The yield rate paradox in closed-loop supply chains

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Abstract

We investigate the dynamics of a closed-loop make-to-stock supply chain consisting of a remanufacturer and a manufacturer with a first-order vector auto-regressive demand and return process. Remanufactured products, considered as-good-as-new, partially satisfy market demand; newly manufactured products fill the remainder. The manufacturer and the remanufacturer cooperate to minimize the sum of the 1) capacity costs at the remanufacturing and manufacturing processes, 2) finished goods inventory holding and backlog cost, 3) cost to dispose of returned items not re-manufactured and 4) collection cost. The remanufacturer inspects returned products in a triage process. Only a predetermined fraction (the triage yield rate) of the returns are re-manufactured. We investigate the impact of the triage yield on the system-wide cost. In a cost-sensitive setting, when the unit cost of remanufacturing is lower than the unit cost of manufacturing, it seems reasonable to conjecture that higher triage yields lead to lower system-wide costs. We show the system-wide cost is always convex in the triage yield rate, suggesting system-wide costs could actually increase in the triage yield rate, even when the unit remanufacturing cost is lower than the manufacturing cost. This *yield rate paradox* originates from the increased yields creating additional variability in the manufacturing activities. By investigating boundary conditions we find the minimal disposal penalty required to entice the remanufacturer to process all returns.

Keywords: Supply Chain Management, Closed-loop Supply Chain, Vector Auto-Regressive Process, Order-Up-To Policy

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1. Introduction

The return and remanufacturing of used products is feasible and socially desirable, but not always economic. While "the first rule in being sustainable is being profitable"[1], Porter and van der Linde (1995) argue cost-sensitive companies are concerned with the conflict between environmental stewardship and economic performance. We aim to identify when a profit maximising company would voluntarily re-manufacture returned products in a closed-loop supply chain (CLSC).

Ferguson and Toktay (2006) argue that often cost-sensitive companies may choose not to re-manufacture due to 1) internal cannibalization and 2) the cost associated with remanufacturing. We focus on the second concern and assume perfect substitution between newly manufactured and re-manufactured products. Assuming perfect-substitution is common when investigating the dynamics of CLSC (e.g. Tang and Naim, 2004; Zhou and Disney, 2006; Hosoda et al., 2015; Zhou et al., 2017; Hosoda and Disney, 2018; Ponte et al., 2020b, 2019). Perfect-substitution is also assumed in economic studies using game theory approaches (e.g. Savaskan et al., 2004; Atasu et al., 2013). While perfect-substitution is not applicable in all settings, it is in some (Goltsos et al., 2019). For example, Suntory, one of the largest beverage companies in Japan, has developed bottle-to-bottle remanufacturing technology for good-as-new PET bottles (Suntory, 2019). In one of the few CLSC studies that does not exploit the good-as-new assumption, Kainuma et al. (2017) study the impact of demand for re-manufactured products cannibalising the demand for new products in a Bass Diffusion model.

To investigate the economic concern, we assume, as did Savaskan et al. (2004) and Kumar Jena and Sarmah (2014), that the unit remanufacturing costs are lower than the unit manufacturing costs. One may think all returned products would be re-manufactured if the remanufacturing cost was less than the manufacturing costs under the perfect substitution assumption. However, sometimes reasonable conjectures underpinned by linear, *forward*, supply chain knowledge are misleading in complex CLSC settings. For example, consider the so-called *lead-time paradox* in CLSC research (van der Laan et al., 1999; Inderfurth and van der Laan, 2001; Zanoni et al., 2006; Hosoda et al., 2015; Hosoda and Disney, 2018), which describes the case when a *longer* remanufacturing lead-time reduces system-wide costs. This is a paradox because, in forward supply chains, *shorter* lead-times typically reduce costs.

We prove the system-wide cost is convex in the yield rate, revealing another paradox exists in CLSCs; under some economic conditions, an incentive to re-manufacture all, or even some, of the returns does not always exist, even if the unit remanufacturing cost is lower than the cost to manufacture new items. Identifying this *yield rate paradox* is the major contribution of our research.

[1] Ellen MacArthur Foundation, "Case Study: Aquafil Group" (PDF file), downloaded from Econyl website, [https://www.econyl.com/assets/uploads/EllenMacArthur_case-study-aquafil-group.pdf], accessed May 27, 2020.

This finding indicates that cost-sensitive organisations face a conflict between economic performance and sustainability, even if remanufacturing is technically feasible. We show that 1) a penalty cost for disposal (charged by municipal authorities, for example), 2) the expected returns, or 3) the unit remanufacturing cost has a significant impact on the nature of the system-wide cost function. The minimum threshold unit disposal cost, large enough to entice complete remanufacturing of returns without creating an unnecessary economic burden, is investigated. Finally, we propose a set of actions that leads the system to a sustainable and economically feasible status.

Our paper is structured as follows: In §2 we review related literature. In §3 we develop our demand and return model and define our system-wide cost function and present some fundamental properties of the demand and return process. §4 introduces our closed-loop replenishment policy and analytically investigates our system-wide objective cost function. §5 presents numerical examples. §6 considers the case of not sharing remanufacturing information within a CLSC. We conclude and consider potential future research directions in §7.

2. Background and related literature

In dynamic CLSC research, some authors argue larger returns reduce costs associated with production, remanufacturing and/or inventory (Zhou and Disney, 2006; Turrisi and Bruccoleri, 2013; Cannella et al., 2016; Zhou et al., 2017), suggesting little regulation or legislation of CLSCs is necessary. Others argue government regulation and legislation is required to induce companies to collect and re-manufacture used products (Tang and Zhou, 2012; Murakami et al., 2015). Hassini et al. (2012) assert many companies remain reluctant to commit to sustainability practices as they see it as an extra operational cost. The major concern seems to be the potential for higher remanufacturing and inventory costs in their CLSC. This concurs with research that concludes the economic impact of returns on CLSCs performance could be negative (Hosoda and Disney, 2018; Ponte et al., 2020b, 2019; Gavidel and Rickli, 2019). For example, Gavidel and Rickli (2019) argue that extremely high return volumes reduce the stability of the remanufacturing system and can increase cost if not efficiently managed.

Under independently and identically distributed (iid) demand and uncorrelated returns, Ponte et al. (2020a) investigate the impact of two different information sharing schemes within a CLSC on the system-wide cost: information about the market pipeline and the remanufacturing pipeline. They show sharing information on the quantity of product being of re-manufactured lowers the system-wide cost, especially when return rate is high, even in the absence of information about the quantity of product in the market. Herein, we assume that full information about the remanufacturing pipeline is shared. We will show sharing remanufacturing information allows for the tightest possible control of the serviceable inventory.

Assuming auto- and cross-correlated demand and returns exist with a random yield rate at the remanufacturer, Hosoda and Disney (2018) show that larger expected returns can increase CLSC inventory costs. Ponte et al. (2020b) illustrate that the relationship between inventory performance and return yield when demand and returns are partially cross-correlated iid random processes. They show that the relationship is a U-shaped; higher return yields lead to higher inventory costs.

Ponte et al. (2019) assert these conflicting conclusions originate in the modelling assumptions made about the market demand and the return processes. Most research assumes simple iid processes for demand and returns, with perfect positive correlation between them. This setting tends to result in over-simplistic conclusions. Consider the following logic; under perfect positive correlation between demand and returns, when demand is high (low), then the returns are also high (low) and such high (low) returns are matched with demand. These two assumptions, the perfect positive correlation and the perfect substitution, generates the situation where in order to satisfy high demand, the manufacturer prefers a higher return rate to a lower return rate. This is especially true if the cost of remanufacturing is lower than the cost of manufacturing. The returns can be used to absorb market demand fluctuations, Zhou and Disney (2006). To quantify the impact of the perfect correlation assumption, Ponte et al. (2019) use partially cross-correlated iid processes for demand and returns. They conclude the dynamic behaviour of a CLSC is strongly influenced by the degree of the cross-correlation between demand and returns. A similar argument can be seen in Hosoda et al. (2015), Braz et al. (2018), and Hosoda and Disney (2018).

The CLSC field is dominated by research that assumes iid demand and returns, (see Tang and Naim, 2004; Zhou and Disney, 2006; Kumar Jena and Sarmah, 2014; Zhou et al., 2017; Hosoda et al., 2015; Ponte et al., 2020b, 2019, for example). In contrast, traditional supply chain research often assumes auto-correlated demands are present (see Kahn, 1987; Lee et al., 2000; Chen et al., 2000; Hosoda and Disney, 2006; Ali et al., 2017, for example). To the best of our knowledge, the first CLSC research relaxing the iid demand and returns assumption is Hosoda and Disney (2018) who used a first order vector auto-regressive process, VAR(1), to represent auto- and cross-correlated demand and returns in a CLSC setting. The VAR(1) model is first proposed by Box and Tiao (1977) and has become an accepted model in forward supply chain research since Kurata et al. (2007) first applied the VAR(1) model to a forward supply chain. They consider the dynamics of a two echelon supply chain consisting of two manufacturers and a supplier. Ratanachote (2011) studied a distribution network design problem with the demands at different distribution centres being represented by a VAR(1) process. Boute et al. (2013) consider the capacity and inventory costs in a multiple product situation that share the same production facility. Raghunathan et al. (2017) identify how a *super bullwhip effect* was produced in a setting with VAR(1) demands. The super bullwhip effect originated from the correlation between the two noise processes, an effect that was also studied by Chaharsooghi and Sadeghi (2008). Sirikasemsuk and Luong (2017) investigated the dynamics of a two-echelon forward supply chain with VAR(1) demand concluding that the performance of the supply chain largely depends on the values of auto- and cross-coefficients. Hosoda and Disney (2018) consider a VAR(1) demand and return process in a CLSC highlighting that not only the cross-correlation parameter, but also the auto-correlation parameters have a significant impact on the production and inventory costs. We continue this VAR(1) modelling approach.

Another issue under-represented in the CLSC literature is worth consideration. To quantify the impact of returns, many authors adopt performance indicators such as the bullwhip ratio (the variance of production divided by the variance of market demand) and/or the net stock amplification ratio, NSAmp (the variance of net stock levels divided by the variance of market demand). See, Braz et al. (2018) for a recent literature review on the bullwhip effect in CLSC, Adenso-Dìaz et al. (2012) for a thoughtful summary of the early bullwhip research in CLSCs, and Tang and Naim (2004), Zanoni et al. (2006), Hosoda et al. (2015), Adenso-Dìaz et al. (2012), Cannella et al. (2016), and Zhou et al. (2017) for specific studies. In linear forward supply chain research, these indicators (bullwhip and NSAmp) are commonly used as a surrogate for actual supply chain costs. However, to the best of our knowledge, these measures have not been verified as good indicators of costs in CLSC settings. Indeed, applying bullwhip and NSAmp indicators in CLSC settings is rather questionable under the perfect substitution assumption. Consider the bullwhip ratio as an example. With perfect-substitution the demand from the market is met jointly by newly produced and re-manufactured products. Thus, the expected demand for the new products is less than the expected market demand. We use the term *net demand* for new product demand. The new production orders are driven only by the net demand, not the market demand. Furthermore, we show later, the variance of the net demand could be greater than the market demand, while the mean of the net demand is less than the mean of the market demand. Given these observations, should we continue to use the variance of *market demand* in the denominators of the bullwhip and NSAmp ratios? We leave this question for future debate; instead we focus on minimising an objective cost function.

Assuming VAR(1) demand and return processes, we investigate whether a cost-sensitive system will voluntarily re-manufacture all of the product returned from the market place. To evaluate the performance of the system, we use the system-wide cost, the sum of the capacity costs at the remanufacturing and manufacturing processes, a finished goods inventory holding and backlog cost, the cost to dispose returned items that are not re-manufactured, and a collection cost. We further assume that the triage yield rate is a decision variable and reveal the system-wide cost is convex in the triage yield rate. This suggests that increased remanufacturing does not always result in a lower system cost, even when the remanufacturing unit cost is lower than the manufacturing unit cost. We call this phenomena the *yield rate paradox*. We investigate boundary conditions for eliminating the yield rate paradox; our analysis culminates in a recommendation for the minimal disposal penalty required to entice the remanufacturer to process all returns.

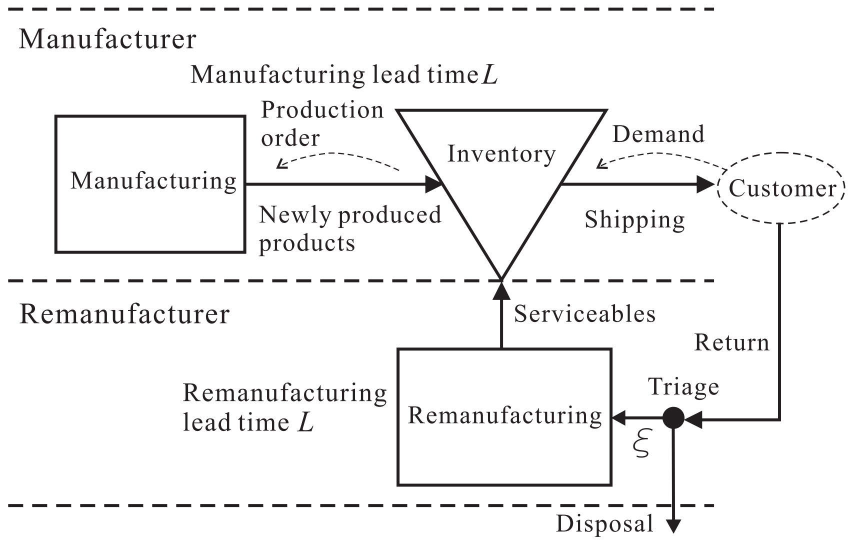

Figure 1: Schematic of the model

3. Preliminary matters

To investigate the yield rate paradox, we develop a stylized model of a closed loop supply chain system consisting of a manufacturer and a remanufacturer, see Fig. 1. Remanufactured products are considered as-good-as-new and stocked to partially satisfy market demand; newly manufactured products make up the remainder. In a recent structured literature review of bullwhip in CLSC, Braz et al. (2018) found the good-as-new assumption to be common. The manufacturer and the remanufacturer cooperate in order to minimize a system-wide cost. The system wide cost consists of capacity costs at the remanufacturing and manufacturing processes, a finished goods inventory holding and backlog cost, a disposal cost, and a collection cost. The returned products are pushed to the remanufacturer and first inspected via a triage process. Tang and Naim (2004), Hosoda et al. (2015) and Ponte et al. (2020b) also exploit the same assumption. A predetermined proportion of the returns is then transferred to the remanufacturing process. This proportion, $0 \leq (\xi \in \mathbb{R}) \leq 1$, is the triage yield and is considered to be a decision variable in our system. Figure 2 illustrates the sequence of events at the manufacturer. At the beginning of time period t, the manufacturer receives new items from its production line as well as serviced items from a remanufacturer. The manufacturer then observes and satisfies the market demand. Unmet demand is backlogged. At the end of each time period t, inventory is observed, re-manufactured returns and demand is tallied, and the manufacturer places a production order to its own production line. This leads to the following balance equation for the serviceable inventory:

$$NS_t = NS_{t-1} + \xi R_{t-(L+1)} + P_{t-(L+1)} - D_t. \tag{1}$$

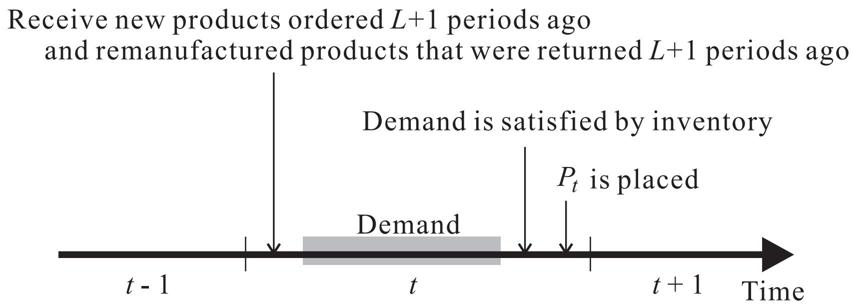

Figure 2: Sequence of events at the manufacturer

Here, NS_t is the net stock level of finished goods at time t, $L \in \mathbb{N}_0$ is the remanufacturing lead time, $R_{t-(L+1)}$ is the returns received by the remanufacturer at time $t-(L+1)$, $\xi R_{t-(L+1)}$ is the re-manufactured products received by the manufacturer at t that have survived the triage process with a time-invariant predetermined yield rate[2] of ξ and will be re-manufactured, $P_{t-(L+1)}$ is the production of new items completed after a production lead time of L and received by the manufacturer at t, and D_t is the demand in time period t. Notice, we assume the lead time to produce new product is the same as the lead time to triage and re-manufacture the returns. This assumption greatly simplifies our analysis. Furthermore, Hosoda and Disney (2018) also show that equal lead times are both sustainable and economically desirable; we leave the case of differing lead times for future research.

The VAR(1) process is assumed for demand and returns. We assume the returns are cross-correlated with the demand but not vice versa; this is a natural assumption as new items entering the market will eventually be returned; but products cannot be returned before the demand has occurred. The VAR(1) market demand and the return processes are defined as:

$$
\begin{aligned}
D_t &= \mu_d + \phi_d(D_{t-1} - \mu_d) + \varepsilon_{d,t}, \\
R_t &= \mu_r + \phi_r(R_{t-1} - \mu_r) + \theta_r(D_{t-1} - \mu_d) + \varepsilon_{r,t}.
\end{aligned}
$$

Here, $\{\mu_d, \mu_r\}$ are the mean demand and mean returns and $\{\varepsilon_{d,t}, \varepsilon_{r,t}\}$ are iid random variables[3] with zero means and constant standard deviations of $\{\sigma_d, \sigma_r\}$. We assume that $\varepsilon_{d,t}$ and $\varepsilon_{r,t}$ are independent of each other. $\{\phi_d, \phi_r\}$ are the auto-correlation coefficients for the demand and returns, and θ_r is the cross-correlation coefficient between demand in the previous period and the mean

[2]One could consider $\xi = \min x, \Xi, where x \in [0,1]$ is the proportion of the returns that are remanufacturable due to quality and/or technical issues and $\Xi \in [0,1]$ is the proportion of products that the system wishes to re-manufacture for economic reasons. To avoid unnecessarily complex notation, we use ξ to represent the yield.

[3]We assume $\{\varepsilon_{d,t}, \varepsilon_{r,t}\}$ are independent of each other as this greatly simplifies the exposition of our results, but we do recognise that the full VAR model allows for these two noise processes to be cross-correlated.

demand. We assume the manufacturer is aware of both D_t and R_t via an information sharing mechanism. Stability conditions require that $|\phi_d| < 1$ and $|\phi_r| < 1$, Boute et al. (2013). Interestingly, stability is independent of θ_r in our setting. While our analytical results hold for all stable systems, we assume that $0 < \{\phi_d, \phi_r\} < 1$ in our numerical analysis. This reflects the fact that most real demand processes have positive auto-regressive parameters (Lee et al., 2000; Hosoda et al., 2008; Ali et al., 2017).

Since we assume perfect substitution between new and re-manufactured products, the *net demand* at time t (ND_t) to be satisfied with newly produced products could be less than D_t. This net demand and its expectation is given by:

$$ND_t = D_t - \xi R_{t-(L+1)},$$

and

$$\mathbb{E}[ND] = \mu_d - \xi \mu_r \ \leq \mu_d,$$

where $\xi R_{t-(L+1)}$ represents the quantity of the re-manufactured serviceable products received by the manufacturer at the beginning of time t. The net demand concept helps us to understand the dynamics of the system. Using the net demand, the inventory balance equation (1) simplifies to

$$NS_t = NS_{t-1} + P_{t-(L+1)} - ND_t. \tag{2}$$

The demand process, D_t, has a variance of,

$$\mathbb{V}[D] = \sigma_d^2/(1-\phi_d^2),$$

Box et al. (2008). Hosoda and Disney (2018) show the variance of the return process, R_t, is,

$$\mathbb{V}[R] = \frac{\sigma_r^2}{1-\phi_r^2} + \frac{\theta_r^2(1+\phi_d\phi_r)}{(1-\phi_d\phi_r)(1-\phi_r^2)}\mathbb{V}[D], \tag{3}$$

the co-variance between the D_t and R_t, cov_0, is

$$\text{cov}_0 = \mathbb{E}[(D_t-\mu_d)(R_t-\mu_r)] = \phi_d\theta_r\mathbb{V}[D]/(1-\phi_d\phi_r),$$

and the co-variance between D_t and $R_{t-(L+1)}$, cov_{L+1}, is

$$\text{cov}_{L+1} = \mathbb{E}[(D_t-\mu_d)(R_{t-(L+1)}-\mu_r)] = \phi_d^{L+1}\text{cov}_0. \tag{4}$$

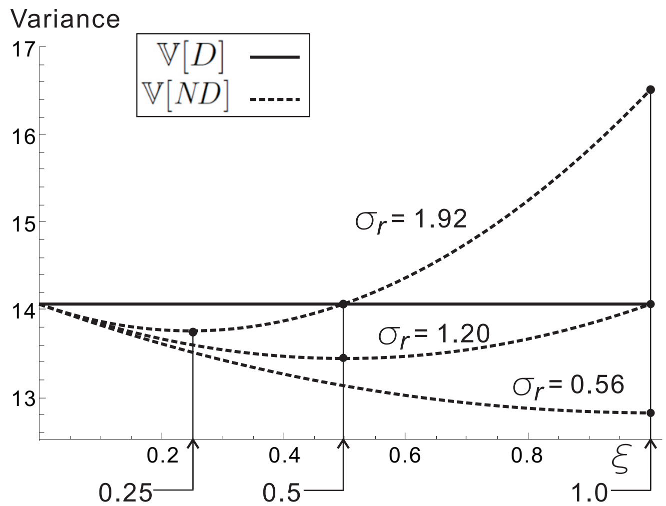

Figure 3: $\mathbb{V}[D]$ and $\mathbb{V}[ND]$ *w.r.t.* ξ when $\sigma_r \in \{0.56, 1.20, 1.92\}$

σ_r	Minimum at $\frac{\text{cov}_{L+1}}{\mathbb{V}[R]}$	$\mathbb{V}[ND] < \mathbb{V}[D]$, when $\xi < 2\frac{\text{cov}_{L+1}}{\mathbb{V}[R]}$
1.92	0.25	0.5
1.20	0.5	1.0
0.56	1.0	2.0

Table 1: Feature values in Fig. 3

Lemma 1 (Variance and characteristics of the net demand)**.** *The variance of the net demand, $\mathbb{V}[ND]$, is:*

$$\mathbb{V}[ND] = \mathbb{V}[D] - 2\xi cov_{L+1} + \xi^2 \mathbb{V}[R] = \mathbb{V}[D]\left(1 - \frac{2\xi\phi_d^{L+2}\theta_r}{1-\phi_d\phi_r}\right) + \xi^2\mathbb{V}[R].$$

If $0 \le \xi \le (2cov_{L+1}/\mathbb{V}[R])$ *holds, then* $\mathbb{V}[ND] \le \mathbb{V}[D]$*. Furthermore, if* $0 \le \xi < (cov_{L+1}/\mathbb{V}[R])$*, $\mathbb{V}[ND]$ is a convex and decreasing function in ξ. $\mathbb{V}[ND]$ is minimized when $\xi = [\min[cov_{L+1}/\mathbb{V}[R], 1]]^+$, where $[x]^+ = \max[0, x]$ is the maximum operator.*

Proof. The proof is shown in Appendix A. □

Remark. The yield rate ξ is a decision variable in our CLSC model that can be used to alter the variance of the net demand, the demand faced by the manufacturer. Both the variance of the demand and returns contribute towards the variance of the net demand. Increasing ξ enhances the contribution of $\mathbb{V}[R]$, and dilutes the contribution of $\mathbb{V}[D]$, to $\mathbb{V}[ND]$.

Some numerical examples of Lemma 1 are shown in Fig. 3 and Table 1. Commonly used parameter values across the all three cases are: $\phi_d = 0.6$, $\phi_r = 0.3$, $\theta_r = 0.2$, $\sigma_d = 3$, and $L = 0$. Depending on the values of parameters, $\mathbb{V}[ND] > \mathbb{V}[D]$ when $(2\text{cov}_{L+1}/\mathbb{V}[R]) < \xi \le 1$ holds, even though $\mathbb{E}[ND] < \mu_d$.

3.1. Objective cost function

We assume the following cost function exists in our CLSC,

$$\begin{aligned} C[\xi] = & \underbrace{\mathbb{E}[h[NS_t]^+ + b[-NS_t]^+]}_{\text{Inventory cost}} + \underbrace{\mathbb{E}[uk + w[P_t - k]^+]}_{\text{Production capacity cost}} + \underbrace{\mathbb{E}[u_r k_r + w_r[\xi R_t - k_r]^+]}_{\text{Remanufacturing capacity cost}} \\ & + \underbrace{\mathbb{E}[A \times R_t]}_{\text{Collection cost}} + \underbrace{\mathbb{E}[G(1-\xi)R_t]}_{\text{Disposal cost}}. \end{aligned} \tag{5}$$

Here h is a unit inventory holding cost and b is a unit inventory backlog cost. The manufacturer (remanufacturer), has an installed capacity of k (k_r). A unit labour cost of u (u_r) is paid for each unit of k, (k_r); if the production (remanufacturing) volume is less than the capacity k (k_r), the labor stands idle and they still receive their nominal weekly wage of uk, $(u_r k_r)$. If the production (remanufacturing) volume is greater than the installed capacity k, (k_r), a unit cost of $w > u$ $(w_r > u_r)$ is additionally paid for the excess. Furthermore, we assume remanufacturing related costs are less than the new product production costs, i.e. $u > u_r$ and $w > w_r$, to encourage the system to remanufacture as many returns as possible. The unit disposal and collection costs are represented by G and A, respectively. The values of G and A do not increase/decrease with the scale of the returns, as in Savaskan et al. (2004) and He et al. (2019). Normally distributed error terms in the VAR(1) process, $\varepsilon_{d,t}$ and $\varepsilon_{r,t}$, mean all the state variables are also normally distributed in our linear system. This leads to the following four Lemmas where $\varphi[\cdot]$ and $\Phi[\cdot]$ are the probability density function and cumulative density function of the standard normal distribution respectively:

Lemma 2 (Inventory costs)**.** *With a safety stock of* $TNS^\star = z_i\sqrt{\mathbb{V}[NS]}$*:* $z_i = \Phi^{-1}[b/(h+b)]$*, the minimised inventory related costs,* $C_I^\star$*, are,*

$$C_I^\star = \min_{TNS}\{\mathbb{E}\left[h[NS_t]^+ + b[-NS_t]^+\right]\} = (h+b)\ \varphi[z_i]\sqrt{\mathbb{V}[NS]}. \tag{6}$$

Proof. The proof of Lemma 2 can be obtained using standard newsvendor techniques (Churchman et al., 1957). A sketch of the proof is also provided in Appendix B. □

Remark. The inventory related costs are independent of ξ.

Lemma 3 (Production costs)**.** *With a capacity of* $k^\star = \mu_d - \xi\mu_r + z_p\sqrt{\mathbb{V}[P]}$ *where* $z_p = \Phi^{-1}\left[(w-u)/w\right]$*, the minimised production costs,* $C_P^\star$*, are,*

$$C_P^\star = \min_k\{\mathbb{E}[uk + w[P_t - k]^+]\} = w\ \varphi[z_p]\sqrt{\mathbb{V}[P]} + u(\mu_d - \xi\mu_r). \tag{7}$$

Proof. The proof is presented in Appendix B. □

Lemma 4 (Remanufacturing cost)**.** *With a capacity of* $k_r^\star = \xi\mu_r + z_r\sqrt{\xi^2\mathbb{V}[R]}$ *where* $z_r = \Phi^{-1}\left[(w_r - u_r)/w_r\right]$*, the minimised remanufacturing costs are,*

$$\min_{k_r}\{\mathbb{E}[u_r k_r + w_r[\xi R_t - k_r]^+]\} = w_r\varphi\left[z_r\right]\sqrt{\xi^2\mathbb{V}[R]} + u_r\xi\mu_r. \tag{8}$$

Proof. The proof is presented in Appendix B. □

Lemma 5 (Collection and disposal costs)**.** *The expected per period costs to collect used products from the market and to dispose of returned items that are not re-manufactured are given by:*

$$\mathbb{E}[A \times R_t] = A\mu_r, \text{ and} \tag{9}$$

$$\mathbb{E}[G(1-\xi)R_t] = G(1-\xi)\mu_r. \tag{10}$$

Proof. These relations are easily obtained by noting $\mathbb{E}[R] = \mu_r$. □

Eqs (6)-(10) lead to the following expression for the total cost in our CLSC,

$$\begin{aligned} C[\xi] =& (h+b)\ \varphi[z_i]\sqrt{\mathbb{V}[NS]} + w\ \varphi[z_p]\sqrt{\mathbb{V}[P]} + u(\mu_d - \xi\mu_r) + \\ & w_r\ \varphi[z_r]\sqrt{\xi^2\mathbb{V}[R]} + u_r\xi\mu_r + G(1-\xi)\mu_r + A\mu_r. \end{aligned} \tag{11}$$

To enumerate $C[\xi]$, we need expressions for $\mathbb{V}[NS]$ and $\mathbb{V}[P]$ ($\mathbb{V}[R]$ was given in (3)), which in turn are dependent upon the forecasting and ordering (replenishment) policies present. In the next section we first define the forecasting and ordering policies; we then derive analytical expressions of those variances.

4. Closed-loop order-up-to (CL-OUT) policy

In this section, we will specify the replenishment policy, a closed-loop order-up-to (CL-OUT) policy, used by the manufacturer to determine the quantity of new products to be manufactured. Similar, but different, policies can be seen in Hosoda et al. (2015) and Hosoda and Disney (2018). The production of new products are generated with an adapted order-up-to policy that accounts for the re-manufactured returns and the pipeline of triaged returns currently being re-manufactured:

$$P_t = \underbrace{\mathbb{E}[ND_{t+L+1}|t]}_{\text{Expected net demand}} + \underbrace{TNS^\star - NS_t}_{\text{Inventory deviation}} + \underbrace{\overbrace{\mathbb{E}\left[\sum_{i=1}^{L} ND_{t+i}|t\right]}^{\text{Target WIP}} - \sum_{i=1}^{L} P_{t-i}}_{\text{Pipeline deviation}}. \tag{12}$$

The expected net demand in the period after the lead-time and review period, conditional upon the information available at time t, is

$$\mathbb{E}[ND_{t+L+1}|t] = \mathbb{E}[D_{t+L+1}|t] - \mathbb{E}[\xi R_t] = \mu_d + \phi_d^{L+1}(D_t - \mu_d) - \xi R_t,$$

where $\mathbb{E}[D_{t+L+1}|t]$ is given by the conditional expectation of AR(1) demand $L+1$ periods ahead, Box et al. (2008). The value of $\mathbb{E}[\xi R_t]$ is known at time t by the manufacturer, as its value was already realized and observed by the remanufacturer and, we assume, shared with the manufacturer. That is, we have full information sharing (Ponte et al., 2020a). The optimal target net stock, $TNS^\star$ was given in Lemma 2. The expected net demand over the lead-time, which serves as a target WIP level, is

$$\mathbb{E}\left[\sum_{i=1}^{L} ND_{t+i}|t\right] = \mathbb{E}\left[\sum_{i=1}^{L} D_{t+i}|t\right] - \sum_{i=1}^{L} \xi R_{t-i} = L\mu_d + \phi_d \frac{1-\phi_d^L}{1-\phi_d}(D_t - \mu_d) - \sum_{i=1}^{L} \xi R_{t-i}.$$

The final sum, $\sum_{i=1}^{L} P_{t-i}$ in (12), is the pipeline of new products currently being produced, aka the work-in-progress.

Lemma 6 (Alternative formulation of the CL-OUT policy)**.** *Our CL-OUT policy,* (12)*, is equivalent to*

$$P_t = D_t - \xi R_t + (S_t - S_{t-1}), \tag{13}$$

where S_t is the OUT level determined at time t described as:

$$S_t = (L+1)\mu_d + \phi_d \frac{1-\phi_d^{L+1}}{1-\phi_d}(D_t - \mu_d) + TNS^\star, \tag{14}$$

which is exactly the same OUT level used in the traditional OUT policy without returns (e.g. Lee et al., 2000; Hosoda and Disney, 2006).

Proof. Eqs. (13) and (14) are derived in Appendix C. □

Remark. Both (12) and (13) generate identical dynamics.

The cost expression (11) requires us to identify the standard deviation of: the inventory levels, the production quantities, and the re-manufactured quantities. The standard deviation of the re-manufactured quantities, $\sqrt{\xi^2 \mathbb{V}[R]}$, is readily obtained from the variance of the returns, (3); the variance of the inventory levels and production quantities are obtained in the following Lemmas:

Lemma 7 (Inventory variance)**.** *The variance of the net stock levels given by CL-OUT policy for* *the case of equal the manufacturing and remanufacturing lead times,* $\mathbb{V}[NS]$*, is*

$$\mathbb{V}[NS] = \frac{(L+1)(1-\phi_d^2)+\phi_d(1-\phi_d^{L+1})(\phi_d^{L+2}-\phi_d-2)}{(1-\phi_d)^2(1-\phi_d^2)}\sigma_d^2. \tag{15}$$

Proof. The proof is shown in Appendix D. □

Remarks. The variance of the net stock levels (15) is independent of $\{\xi,\ \phi_r,\ \theta_r,\ \sigma_r\}$, the return and the triage parameters. Thus, inventory related costs (6) are not influenced by the triage yield ξ and the uncertainty in the returns, $\varepsilon_{r,t}$. As the value of $P_{t-(L+1)}$ is known, the only uncertainty that affects NS_t comes from the market demand, D_t. This means, the variance of the inventory levels in our CLSC model is the same as the variance of the inventory levels in a traditional supply chain with AR(1) demand (see Lee et al., 2000; Hosoda and Disney, 2006, for example). In contrast, the variance of the production of new items is different from the traditional supply chain variance as the production quantity must also account for the quantity of the re-manufactured returns.

Lemma 8 (Production variance)**.** *The variance of the production of new items,* $\mathbb{V}[P]$*, is*

$$\mathbb{V}[P] = \mathbb{V}[ND]+\mathbb{V}[D]\frac{2\phi_d(1-\phi_d^{L+1})(1-\phi_d^{L+2})}{1-\phi_d} \tag{16}$$

$$= \xi^2\mathbb{V}[R]+\mathbb{V}[D]\left(1-\frac{2\xi\phi_d^{L+2}\theta_r}{1-\phi_d\phi_r}+\frac{2\phi_d(1-\phi_d^{L+1})(1-\phi_d^{L+2})}{1-\phi_d}\right). \tag{17}$$

The first- and the second-order derivatives of $\mathbb{V}[P]$ *are identical to those of* $\mathbb{V}[ND]$*:*

$$\frac{d\mathbb{V}[P]}{d\xi} = \frac{d\mathbb{V}[ND]}{d\xi} = 2(\xi\mathbb{V}[R]-cov_{L+1}), \tag{18}$$

and

$$\frac{d^2\mathbb{V}[P]}{d\xi^2} = \frac{d^2\mathbb{V}[ND]}{d\xi^2} = 2\mathbb{V}[R] > 0. \tag{19}$$

Proof. The required variance expression and its derivatives are derived in Appendix E. □

Remark. $\mathbb{V}[P] \geq \mathbb{V}[ND]$, if $\phi_d \geq 0$. The difference between $\mathbb{V}[P]$ and $\mathbb{V}[ND]$, $\mathbb{V}[P]-\mathbb{V}[ND]$, is independent of the return and the triage parameters, $\{\xi,\ \phi_r,\ \theta_r,\ \sigma_r\}$, and constant when $\{\phi_d,\ L,\ \sigma_d\}$ remain unchanged. We also note from (16) that if the first addend, $\mathbb{V}[ND]$, was replaced by $\mathbb{V}[D]$, then we would recover the variance of a traditional supply chain, Disney and Lambrecht (2008). The derivatives of $\mathbb{V}[P]$ in Lemma 8 are identical to the derivatives of $\mathbb{V}[ND]$ in Lemma 1, suggesting that $\mathbb{V}[P]$ and $\mathbb{V}[ND]$ are governed by the same mechanism. Interestingly, increasing the triage

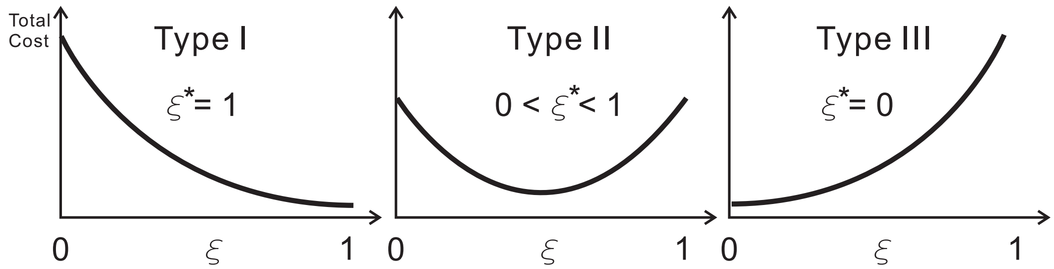

Figure 4: Types of cost curve: Type I: $\xi^* = 1$, Type II: $0 < \xi^* < 1$, and Type III: $\xi^* = 0$

yield ξ does not always reduce the variability of the production, in contrast to the results of Zhou and Disney (2006) and Ponte et al. (2020b).

Bringing together (6)-(10), the objective cost function under CL-OUT policy, (5), can be rewritten as

$$C[\xi] = \mathbb{E}\left[h[NS_t]^+ + b[-NS_t]^+\right] + \mathbb{E}[A \times R_t] + \min_{\xi}\{f[\xi]\} \tag{20}$$

where $f[\xi] = \mathbb{E}[uk + w[P_t - k]^+] + \mathbb{E}[u_r k_r + w_r[\xi R_t - k_r]^+] + \mathbb{E}[G(1-\xi)R_t]$. Eq. (20) reveals the impact of ξ on the system-wide cost is limited to the manufacturing, remanufacturing and disposal costs only; the inventory cost and the collection cost are independent of ξ. Substituting the variances, $\mathbb{V}[NS]$, $\mathbb{V}[P]$, and $\mathbb{V}[R]$, into (11) yields the following Proposition:

Proposition 1 (Convexity of the cost function)**.** *Under the CL-OUT policy, the system-wide cost,* (11) *or* (20)*, is convex in the triage yield rate* ξ.

Proof. Appendix B shows the second-order derivative of (11) and (20) *w.r.t.* ξ is always positive, indicating convexity. □

Proposition 1 indicates the shape of the system-wide cost curve can be categorised into three different types, see Fig. 4. Type I is the ideal case as the value of ξ^* which minimises the system-wide cost is unity; this not only minimises the system-wide cost, but is also good for sustainability. In contrast, Type III is the worst case; no remanufacturing (i.e. $\xi^* = 0$) is most economic. In a type II setting, only a portion of the returns $0 < \xi^* < 1$ are re-manufactured.

Lemma 9 (Types of cost functions)**.** *If the first-order derivative of the cost function satisfies:*

$$\left.\frac{dC[\xi]}{d\xi}\right|_{\xi \to 1} \leq 0, \tag{21}$$

then the cost function curve is Type I and $\xi^* = 1$. *If the first-order derivative of the cost function* *satisfies:*

$$\left.\frac{dC[\xi]}{d\xi}\right|_{\xi\to 0} \geq 0, \tag{22}$$

then the cost function curve is Type III and $\xi^* = 0$*. If neither* (21) *or* (22) *hold, the cost function is Type II and* $0 < \xi^* < 1$.

Proof. It is obvious from Lemma 9 when Type I and Type III cost curves exist. As the set of total costs curves in Fig. 4 is exhaustive, if $(dC[\xi]/d\xi)|_{\xi\to 1} > 0$ and $(dC[\xi]/d\xi)|_{\xi\to 0} < 0$ then Type II cost curves must be present. □

Lemma 10 (Inducing a change in cost function type)**.** *The value of the first derivative of* $C[\xi]$*,* $dC[\xi]/d\xi$*, is decreasing in* μ_r *and* $(u-u_r)$ *when* $u > u_r$*.*

Proof. It is obvious from (B.6) in Appendix B. □

Lemma 10 suggests that larger average returns, μ_r, and/or a larger $(u-u_r)$, will shift the cost function curve from Type III (II) to Type II (I).

Corollary 1 (Minimum disposal cost)**.** *A Type III supply chain exists if the unit disposal cost* $G \leq \underline{G}$*:*

$$G \leq \underline{G} = \frac{w_r}{\mu_r}\,\varphi[z_r]\sqrt{\mathbb{V}[R]} - (u-u_r) - \frac{w}{\mu_r}\,\varphi[z_p]\,\frac{cov_{L+1}}{\sqrt{\mathbb{V}[P]|_{\xi\to 0}}}.$$

A Type I supply chain exists if the disposal cost $G \geq \overline{G}$*:*

$$G \geq \overline{G} = \frac{w_r}{\mu_r}\,\varphi[z_r]\sqrt{\mathbb{V}[R]} - (u-u_r) + \frac{w}{\mu_r}\,\varphi[z_p]\,\frac{\mathbb{V}[R] - cov_{L+1}}{\sqrt{\mathbb{V}[P]|_{\xi\to 1}}}.$$

A Type II supply chain exists if the disposal cost, G, satisfies:

$$\underline{G} < G < \overline{G}.$$

Proof. Corollary 1 is easily obtained from Lemma 9 with the knowledge of (B.6). □

In the next section, we highlight some useful characteristics of the system based on Proposition 1, Lemma 10, and Corollary 1.

5. Numerical investigations

All of the values of parameters used in this section are shown in Table 2. Figure 5 illustrates the impact of G on Case 1, highlighting that as G increases, the cost curve migrates from a Type III

Table 2: Parameter values used in each case

<table>
<tr><th></th><th>Collection Cost</th><th colspan="3">Demand</th><th colspan="4">Return</th></tr>
<tr><th></th><th>A</th><th>μ_d</th><th>ϕ_d</th><th>σ_d</th><th>μ_r</th><th>ϕ_r</th><th>θ_r</th><th>σ_r</th></tr>
<tr><td>Case 1</td><td rowspan="4">1</td><td rowspan="4">20</td><td rowspan="4">0.4</td><td rowspan="4">3</td><td>10</td><td rowspan="4">0.7</td><td rowspan="4">0.5</td><td rowspan="4">1</td></tr>
<tr><td>Case 2</td><td>15</td></tr>
<tr><td>Case 3</td><td>10</td></tr>
<tr><td>Case 4</td><td>15</td></tr>
<tr><th></th><th colspan="2">Inventory Cost</th><th colspan="2">Manu. Cost</th><th colspan="2">Re-manu. Cost</th><th colspan="2">Lead Time</th></tr>
<tr><th></th><th>h</th><th>b</th><th>w</th><th>u</th><th>w_r</th><th>u_r</th><th colspan="2">L</th></tr>
<tr><td>Case 1</td><td rowspan="4">1</td><td rowspan="4">9</td><td rowspan="4">11</td><td rowspan="4">4</td><td rowspan="4">9</td><td rowspan="2">3</td><td rowspan="4" colspan="2">1</td></tr>
<tr><td>Case 2</td></tr>
<tr><td>Case 3</td><td rowspan="2">2.5</td></tr>
<tr><td>Case 4</td></tr>
</table>

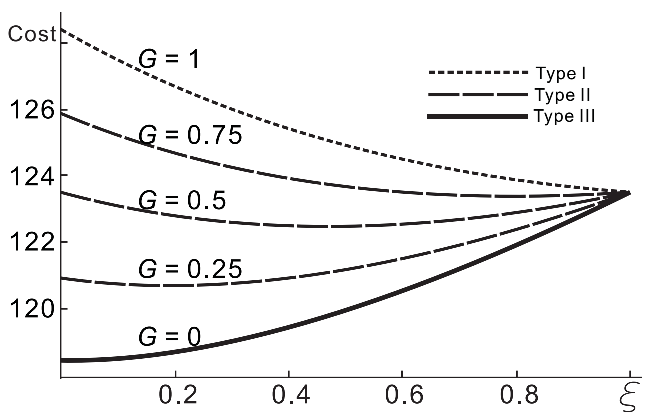

Figure 5: Total cost *w.r.t.* ξ in Case 1

Table 3: Types of supply chain for each G

Case 1	$\underline{G} = 0.058$	$\overline{G} = 0.886$	Type
$G = 0$	$G < \underline{G}$		III
$G = 0.25$	$\underline{G} < G < \overline{G}$		II
$G = 0.5$	$\underline{G} < G < \overline{G}$		II
$G = 0.75$	$\underline{G} < G < \overline{G}$		II
$G = 1$	$\overline{G} < G$		I

curve to a Type II curve through to a Type I curve. Table 3 contains the threshold values $\overline{G}$ and $\underline{G}$ presented in Corollary 1. As shown in Fig. 5, the disposal penalty cost G influences the type of the supply chain. If the value of G is determined properly, all supply chains can become Type I. While larger G might be good for the sustainability, it may reduce economic competitiveness. Key factors involved in this trade-off are μ_r, σ_r, and $(u - u_r)$.

Figure 6 illustrates the relationship between μ_r to $\underline{G}$, and $\overline{G}$ for Case 1 shown in Table 2. Both $\underline{G}$ and $\overline{G}$ are decreasing functions in μ_r. When G is above $\overline{G}$, everything returned should be re-manufactured (Type I). When G is below $\underline{G}$, nothing should be re-manufactured (Type III). When G is between the two lines, we have a Type II CLSC and only a proportion of returns should be re-manufactured. Fig. 6 suggests systems with large μ_r may naturally be Type I supply chain without the need for imposing a disposal penalty.

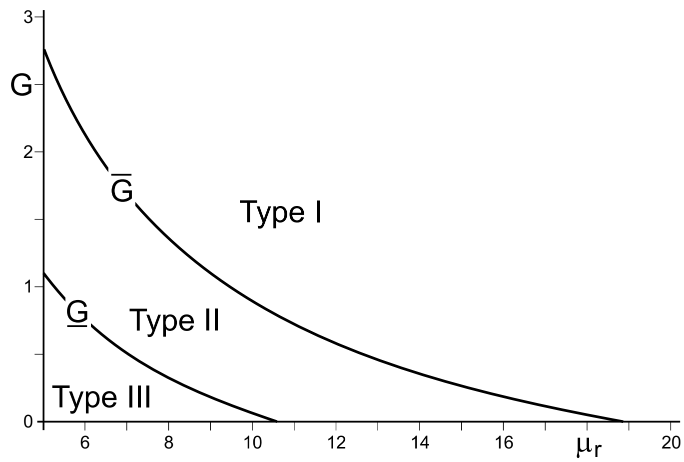

Figure 6: The relationship between the mean returns and the disposal cost required to ensure sustainable operation (Numerical setting for Case 1, see Table 2)

Figure 7 shows the relationship among σ_r, μ_r, $\underline{G}$, and $\overline{G}$. Smaller σ_r result in smaller values of $\underline{G}$ and $\overline{G}$, even though μ_r remains constant. Further reductions of $\underline{G}$ and $\overline{G}$ can be achieved by increasing μ_r. Thus, increasing expected returns and minimizing the variability of those returns is key to inducing a Type I supply chain where sustainability and economic competitiveness are achieved simultaneously.

Let us consider the impacts of μ_r and $(u - u_r)$ on shape of the cost curve when $G = 0$. Fig. 8 highlights some numerical results; feature values, such as $\{\underline{G}, \overline{G}\}$, are highlighted in Table 4. All cost curves in Fig. 8 are convex in ξ, but the nature of their slopes depends upon the parameters. Consider Case 1 (which is Type III) as the base case, the cost-conscious system has no incentive to re-manufacture the returns (i.e. $\xi^* = 0$). If the system faces larger expected returns, μ_r (Case 2), the supply chain becomes Type II; however, the system-wide cost is almost always greater than that in Case 1, due to the higher collection cost. Any additional increases in the disposal penalty only deteriorates the economic competitiveness of the business. If a cost-conscious system in Case 1 exerts some effort to reduce its remanufacturing cost u_r without changing the value of μ_r, the system shifts to Case 3. In Case 3, the supply chain becomes Type II where a portion of the returns is voluntarily re-manufactured and the minimum system-wide cost is lower than that in Case 1. Further cost reduction and higher sustainability can be achieved by having larger expected returns (μ_r). Case 4, a Type I supply chain, has an economic incentive to naturally re-manufacture all the returns (i.e. $\xi^* = 1$) and imposing a disposal cost is not necessary (i.e. $G = 0$).

Based on the insights obtained from Figs. 5 and 8, Fig. 9 illustrates some potential improvement actions that would be agreeable for both the cost-conscious system and policy-makers. The upper-left Panel A in Fig. 9 is considered to be the base case (with the values of parameters used herein are the same as Case 1 shown in Table 2). There is no disposal cost, $G = 0$, and a Type III system

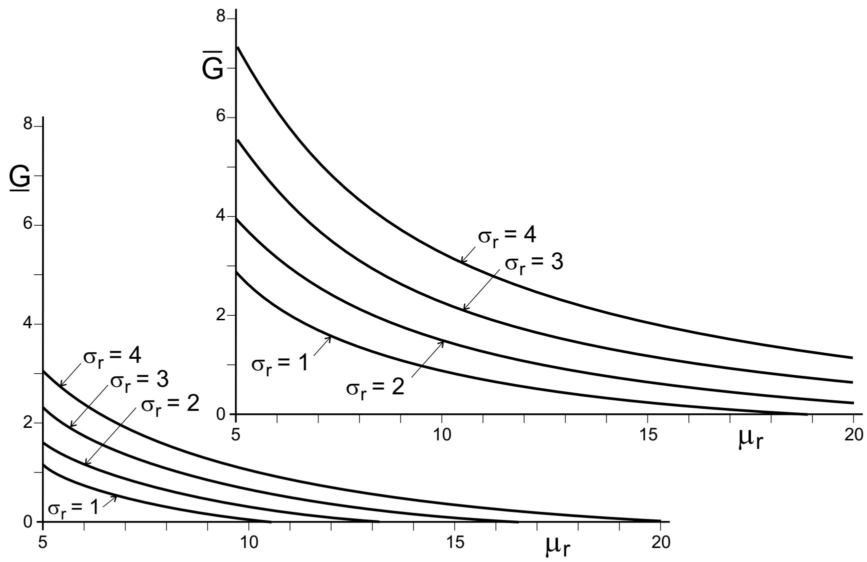

Figure 7: Increasing the variance of the returns (via the standard deviation of the errors in returns = σ_r) inflates both $\underline{G}$ and $\overline{G}$ (Numerical setting for Case 1, see Table 2)

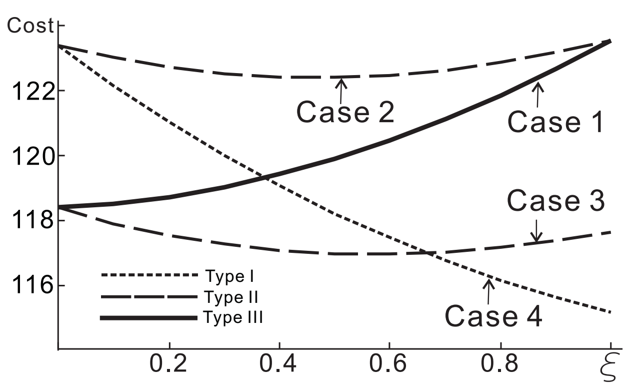

Figure 8: Total cost *w.r.t.* ξ for each case when $G = 0$

Table 4: Feature values used in Fig. 8

$G = 0$	$\underline{G}$	$\overline{G}$	Type	μ_r	$u - u_r$
Case 1	0.058	0.886	III	10	1
Case 2	-0.295	0.258	II	15	1
Case 3	-0.528	0.301	II	10	1.5
Case 4	-0.852	-0.299	I	15	1.5

exists. Costs are minimised with no remanufacturing. In order to improve environmental and economic performance, the system needs to both increase the expected returns, μ_r, and reduce the unit manufacturing cost, u_r, in order to become a Type I system, see Panel D. Doing either of these actions alone induces the base case to become a Type II system; increasing the expected returns alone is shown in Panel B, where minimised costs have increased. Decreasing the remanufacturing cost alone is shown in Panel C, where the reduced u_r has reduced the minimum costs compared to the base case.

Alternatively, if the policymaker was to impose a small disposal cost, $G = 0.5$, the base case Type III system in Panel A is transformed into a Type II system, increasing costs, but enticing the re-manufacture of all returned items, see Panel E. Increasing expected returns alone increases costs, but will induce Type I behaviour, see Panel F; reducing remanufacturing costs induces Type I behaviour and reduces costs, see Panel G. Doing both together in the presence of a small disposal penalty reduces costs even further in the Type I system in Panel H.

Increasing the disposal penalty, $G = 1$, increases the total costs, but enhances the attractiveness of Type I operation, Panels I-L. However, close inspection of the Type I systems, with the same μ_r and u_r (looking along the rows) have identical minimal costs at $\xi^\star = 1$. Compare, for example Panels D, H and L. This indicates higher disposal penalties induce companies to increase returns and reduce remanufacturing costs. If this is done successfully, all the returns are re-manufactured and there is no undesirable economic burden from the disposal penalty.

6. Extension: The cost of not sharing re-manufacturing information

Ponte et al. (2020a) consider the impact of not sharing information of the quantity being re-manufactured with the manufacturer of new product under iid demand and returns. We now extend our analysis to consider the impact of no information sharing (NIS) in our CLSC with VAR(1) demand and returns. From (12), the OUT policy without information sharing becomes,

$$P_t = \underbrace{\mathbb{E}[D_{t+L+1}|t] - \xi\mu_r}_{\text{Expected net demand}} + \underbrace{TNS^\star - NS_t}_{\text{Inventory deviation}} + \underbrace{\overbrace{\mathbb{E}\left[\sum_{i=1}^{L} D_{t+i}|t\right] - L\xi\mu_r}^{\text{Target WIP}} - \sum_{i=1}^{L} P_{t-i}}_{\text{Pipeline deviation}}. \tag{23}$$

Alternatively, the OUT policy without information sharing based on (13) is,

$$P_t = D_t - \xi R_{t-(L+1)} + (S_t - S_{t-1}), \tag{24}$$

where S_t is already described in (14), the OUT level determined at time t. Details to obtain (24) are shown in Appendix C. Note that both (23) and (24) generate the same dynamics. The variance of

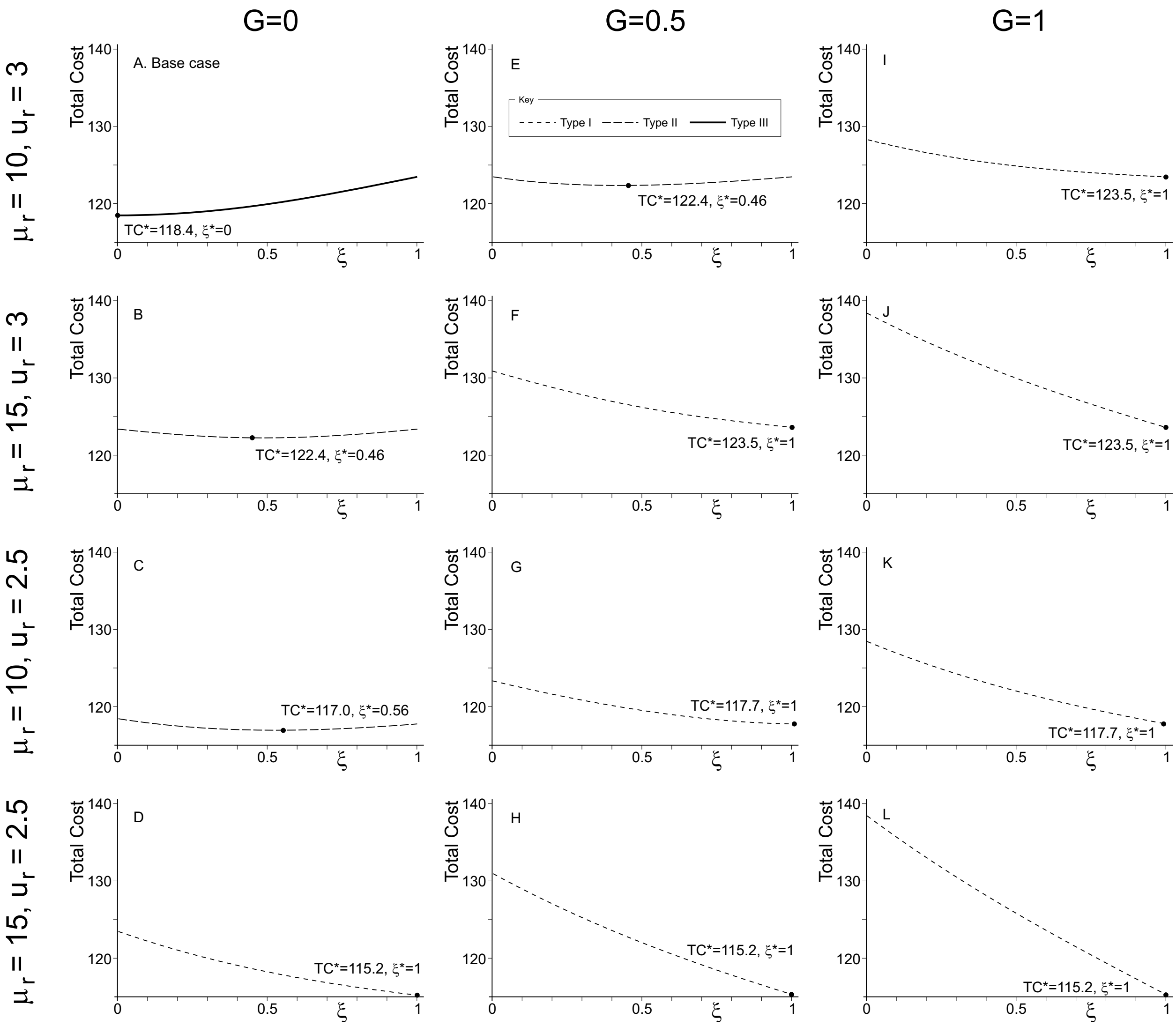

Figure 9: System-wide cost *w.r.t.* ξ and the impact of parameters μ_r, u_r and G

the production without information sharing is given by:

$$
\begin{aligned}
\mathbb{V}[P_{\text{NIS}}] =& \frac{\sigma_d^2\left(1-2\phi_d^{L+2}\right)}{(\phi_d-1)^2} - \frac{\xi^2\sigma_r^2}{(\phi_r-1)(\phi_r+1)} - \frac{\theta_r^2\xi^2\sigma_d^2(\phi_d\phi_r+1)}{\left(\phi_d^2-1\right)\left(\phi_r^2-1\right)(\phi_d\phi_r-1)} + \\
& \frac{2\sigma_d^2\phi_d^{2L+3}(\theta_r\xi(1-\phi_d)+\phi_d(\phi_d\phi_r-1))}{(\phi_d-1)^2(\phi_d+1)(\phi_d\phi_r-1)} \\
=& \xi^2\mathbb{V}[R] + \mathbb{V}[D]\left(\frac{1+\phi_d}{1-\phi_d} - \frac{2\xi\phi_d^{2L+3}\theta_r}{1-\phi_d\phi_r} + \frac{2\phi_d\left((1-\phi_d^{L+1})(1-\phi_d^{L+2})-1\right)}{1-\phi_d}\right) \\
=& \mathbb{V}[P] + 2\xi\,\text{cov}_{L+1}(1-\phi_d^{L+1}).
\end{aligned}
\tag{25}
$$

Notice, $\mathbb{V}[P_{\text{NIS}}] > \mathbb{V}[P]$ iff $\xi\text{cov}_{L+1} > 0$. $\text{cov}_{L+1} = \phi_d^{L+2}\theta_r\mathbb{V}[D]/(1-\phi_d\phi_r)$ was given in (4), and is positive if $\{\phi_d, \phi_r, \theta_r\} > 0$, but may be negative otherwise. There is also an odd-even lead time effect when $\phi_d < 0$. Furthermore, in the case of iid demand and returns (i.e., $\phi_d = \phi_r = 0$), $\mathbb{V}[P_{\text{NIS}}] = \mathbb{V}[P]$, leading to a conclusion that availability of the remanufacturing information does not have an impact on $C_P^\star$ and the bullwhip ratio in the uncorrelated case.

The variance of the net stock without information sharing is given by:

$$
\begin{aligned}
\mathbb{V}[NS_{\text{NIS}}] =& \mathbb{V}[NS] + \sigma_d^2\xi^2\theta_r^2\sum_{n=1}^{\infty}\left(\frac{1}{(\phi_d-1)(\phi_r-1)} - \frac{h[n-L-2]}{\phi_d-1}\left(\frac{\phi_d^{n-L}}{\phi_d-\phi_r} + \frac{1}{\phi_r-1}\right) - \right. \\
& \left. \frac{\phi_r^{n-L}\left(\phi_r^{L+1}-\theta_r(n-L-2)\right)}{(\phi_r-1)(\phi_d-\phi_r)} + \frac{\phi_d^{n+1}}{(\phi_d-1)(\phi_d-\phi_r)}\right)^2 + \\
& \sigma_r^2\xi^2\sum_{n=L+1}^{\infty}\left(\frac{\phi_r^{-2L-1}\left(\phi_r^{L+1}\left(\phi_r^L-\phi_r^n\right)+h[n-2L-2]\left(\phi_r^n-\phi_r^{2L+1}\right)\right)}{1-\phi_r}\right)^2,
\end{aligned}
$$

It might be worth checking the equations in this section as I have made several simplifications to them where $h[x]$ is the Unit Step function; $h[x] = 1$ if $x \in \mathbb{Z}_0$, otherwise $h[x] = 0$. In the above the first addend is the variance of the inventory levels in our the CLSC with information sharing. The second addend is the influence of ε_d on the inventory variance. The third addend is the influence of ε_r on the inventory variance. Both sums are positive (as they are sums of squared functions), which shows that the inventory variance without information sharing is greater than with information sharing. Thus $\mathbb{V}[NS_{\text{NIS}}] > \mathbb{V}[NS]$ must always hold. Closing the sums results in:

$$\begin{aligned}\mathbb{V}[NS_{\text{NIS}}] =& \mathbb{V}[NS] + \sigma_d^2 \xi^2 \theta_r^2 \left(\frac{\phi_d^2 - 6\phi_d + 1}{4(1-\phi_d)^4(1-\phi_r)} + \frac{4\phi_d^3}{(1-\phi_d)^4(1+\phi_d)^2(1-\phi_d\phi_r)} - \right. \\ & \frac{1}{(1-\phi_d)^2(1-\phi_r)^3} + \frac{1}{4(1+\phi_d)^2(1+\phi_r)} + \frac{3+2L}{2(1-\phi_d)^2(1-\phi_r)^2} + \\ & \left. \frac{2\left((1-\phi_r)^3(1+\phi_r)\phi_d^{L+3} - (1-\phi_d)^3(1+\phi_d)\phi_r^{L+3}\right)}{(1-\phi_d)^3(1+\phi_d)(1-\phi_r)^3(1+\phi_r)(\phi_d-\phi_r)(1-\phi_d\phi_r)} \right) + \\ & \sigma_r^2 \xi^2 \left(\frac{\left(L(1-\phi_r^2) + \phi_r(2\phi_r^{L+1} - \phi_r - 2) + 1\right)}{(1-\phi_r)^3(1+\phi_r)} \right). \end{aligned} \tag{26}$$

When the demand and the returns are iid process, $\mathbb{V}[NS_{\text{NIS}}]$ becomes:

$$\mathbb{V}[NS_{\text{NIS}}] = \mathbb{V}[NS] + \xi^2 \sigma_r^2 (L+1),$$

which is greater than $\mathbb{V}[NS]$ when $\xi > 0$. This shows sharing remanufacturing information always reduces $C_I^\star$, even in the iid demand and return case. However, its impact on $C_P^\star$ is not so simple: it could be positive or negative, depending on the values of parameters in the demand and the return processes. Furthermore, assuming iid demand and returns limits the insights that can be obtaining regarding information sharing in CLSCs.

7. Concluding remarks

We investigated the dynamics of a closed-loop make-to-stock system consisting of a remanufacturer and a manufacturer with a VAR(1) demand and return process. We showed that cost-sensitive organisations could face a conflict between economic performance and sustainability and may not always wish to re-manufacture all of the returns, even though the unit cost of remanufacturing is less than that of new products. This is because the system-wide cost in our CLSC is convex in the triage yield rate. This finding suggests the system-wide cost could increase in the triage yield. This yield rate paradox calls for more research effort to be devoted to the problem of making sustainable operations economically viable. We have also identified the threshold disposal cost that determines the slope of the system-wide cost, together with the criteria that led to a more sustainable outcome. Furthermore, we introduced a concept of the net demand and highlighted its importance when perfect substitution is present. We argued the need for new production is strongly affected by net demand, rather then the market demand.

In our CLSC with full information sharing, the inventory levels were not affected by the yield rate. However, convexity of system-cost in the triage yield means there exists an optimal yield rate that minimises total cost. This arises as remanufacturing alters the demand for new product and thus their cost to manufacture. Managers should therefore carefully identify the likely impact of remanufacturing on existing production. We suspect the benefit from introducing remanufacturing activities will be highly influenced by the demand and return process, the lead-times, and the level of information sharing.

Future potential research could investigate: 1) the case where a full VAR(1) demand and return model is assumed, 2) the role of the net demand in the dynamics of the closed-loop supply chain, 3) the impact of different lead times at the remanufacturing and manufacturing sites, 4) the role of the bullwhip ratio and NSAmp as cost indicators in CLSC settings, 5) the impact of the moments of demand and production on the purchasing price of raw materials, and 6) the impact of the information sharing on the economic performance with non-iid demand and return processes assumption.

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Appendix A. Derivation of the variance and characteristics of the net demand

Since the mean of the net demand is $\mathbb{E}[ND] = \mu_d - \xi\mu_r$, the variance of the net demand is:

$$\begin{aligned}\mathbb{V}[ND] =&\mathbb{E}\left[(ND_t - (\mu_d - \xi\mu_r))^2\right] \\ =&\mathbb{V}[D] - 2\xi\mathbb{E}[(D_t - \mu_d)(R_{t-(L+1)} - \mu_r)] + \xi^2\mathbb{V}[R] \\ =&\mathbb{V}[D] - 2\xi\mathrm{cov}_{L+1} + \xi^2\mathbb{V}[R]. \end{aligned} \quad (A.1)$$

The variance expression obtained in (A.1) reveals when $\xi = 0$, $\mathbb{V}[ND] = \mathbb{V}[D]$. When $\xi > 0$ and $\xi^2\mathbb{V}[R] - 2\xi\mathrm{cov}_{L+1} \leq 0$ (or, equivalently, when $0 < \xi \leq 2\mathrm{cov}_{L+1}/\mathbb{V}[R]$ holds, $\mathbb{V}[ND] \leq \mathbb{V}[D]$.

The first- and second-order derivatives of $\mathbb{V}[ND]$ *w.r.t.* ξ are:

$$\frac{d\mathbb{V}[ND]}{d\xi} =2(\xi\mathbb{V}[R] - \mathrm{cov}_{L+1}), \text{ and } \frac{d^2\mathbb{V}[ND]}{d\xi^2} = 2\mathbb{V}[R] > 0.$$

From the first-order derivative, it is obvious that if $0 \leq \xi < (\mathrm{cov}_{L+1}/\mathbb{V}[R])$, $\mathbb{V}[ND]$ is decreasing in ξ. As $0 \leq \xi \leq 1$ and the second-order derivative of $\mathbb{V}[ND]$ is always positive, we can minimize $\mathbb{V}[ND]$ by setting $\xi = [\min[\mathrm{cov}_{L+1}/\mathbb{V}[R], 1]]^+$.

Appendix B. Cost functions for the CL-OUT policy

Inventory costs: The inventory holding and backlog costs can be written as

$$C_{ns} = \mathbb{E}\left[h[NS_t]^+ + b[-NS_t]^+\right] = h\int_0^{+\infty} yf[y]dy + b\int_{-\infty}^{0}(-y)f[y]dy, \quad \text{(B.1)}$$

where $f[\cdot]$ is the normal PDF with the mean, TNS and variance $\mathbb{V}[NS]$. Evaluating the integrals and using the pdf and cdf of the standard normal distribution, $\{\phi[\cdot],\Phi[\cdot]\}$, leads to,

$$C_{ns} = (b+h)\left(TNS\Phi\left[\frac{TNS}{\sqrt{\mathbb{V}[NS]}}\right] + \sqrt{\mathbb{V}[NS]}\phi\left[\frac{TNS}{\sqrt{\mathbb{V}[NS]}}\right]\right) - bTNS \quad \text{(B.2)}$$

We wish to control the target net stock (TNS) to minimise the expected inventory costs. The derivative of C_{ns} w.r.t. TNS is

$$\frac{dC_{ns}}{dTNS} = (b+h)\Phi\left[\frac{TNS}{\sqrt{\mathbb{V}[NS]}}\right] - b. \quad \text{(B.3)}$$

Setting the derivative to zero and solving for TNS reveals the optimal target net stock, $TNS^\star$,

$$TNS^\star = \sqrt{\mathbb{V}[NS]}\Phi^{-1}\left[\frac{b}{b+h}\right]. \quad \text{(B.4)}$$

Using (B.4) in (B.2) and simplifying leads to the following expression for the minimised costs,

$$C^\star_{ns} = (h+b)\varphi\left[\Phi^{-1}\left[\frac{b}{b+h}\right]\right]\sqrt{\mathbb{V}[NS]}. \quad \text{(B.5)}$$

Production costs: The manufacturing cost for the new products, C_p, with the manufacturing capacity, k, can be written as:

$$C_p = w\,\mathbb{E}[[P_t - k]^+] + uk = w\int_k^{+\infty}(y-k)f[y]dy + uk.$$

Here $f[\cdot]$ is the normal PDF with the mean and the variances of P_t. The first- and second-order derivatives of C_p *w.r.t.* k are:

$$\frac{dC_p}{dk} = -w(1-F[k])) + u, \text{ and } \frac{d^2C_p}{dk^2} = wf[k] > 0,$$

where $F[\cdot]$ is the normal CDF with the mean and the variance of P_t. The minimizer of C_p, $k^\star$, should satisfy:

$$F[k^\star] = \frac{w-u}{w} = \Phi\left[\frac{k^\star - \mathbb{E}[P]}{\sqrt{\mathbb{V}[P]}}\right],$$

where $\Phi[\cdot]$ is the standard normal CDF. Since $\mathbb{E}[P] = \mu_d - \xi\mu_r$ as shown in (C.6), $k^\star$ is:

$$k^\star = \mu_d - \xi\mu_r + z_p\sqrt{\mathbb{V}[P]},$$

where $z_p = \Phi^{-1}[(w-u)/w]$. The minimum manufacturing cost, $C_p^\star$, is achieved with the optimum capacity $k^\star$,

$$C_p^\star = w\int_{k^\star}^{+\infty}(y-k^\star)f[y]dy + uk^\star.$$

The integral can be simplified as:

$$w\int_{k^\star}^{+\infty}(y-k^\star)f[y]dy = w\sqrt{\mathbb{V}[P]}\,L[z_p],$$

where $L[\cdot]$ is the standard normal loss function. Simplification yields the stated expression for $C_p^\star$:

$$\begin{aligned} C_p^\star &= w\sqrt{\mathbb{V}[P]}\,L[z_p] + uk^\star \\ &= w\sqrt{\mathbb{V}[P]}\left(\underbrace{L[z_p] + (1-\Phi[z_p])z_p}_{=\varphi[z_p]} + \underbrace{(1-\Phi[z_p])}_{=u/w}\frac{\mu_d - \xi\mu_r}{\sqrt{\mathbb{V}[P]}}\right) \\ &= w\,\varphi[z_p]\sqrt{\mathbb{V}[P]} + u(\mu_d - \xi\mu_r). \end{aligned}$$

Remanufacturing costs: Following the same steps shown above, we obtain the optimal capacity for the remanufacturing, $k_r^\star$, and the minimum remanufacturing cost, $C_r^\star$:

$$\begin{aligned} k_r^\star &= \xi\mu_r + z_r\sqrt{\xi^2\mathbb{V}[R]}, \\ C_r^\star &= w_r\,\varphi[z_r]\sqrt{\xi^2\mathbb{V}[R]} + u_r\xi\mu_r, \end{aligned}$$

where $z_r = \Phi^{-1}[(w_r-u_r)/w_r]$.

Total costs: With the knowledge of $\mathbb{V}[NS]$, $\mathbb{V}[P]$ and $\mathbb{V}[R]$, the cost function for the CL-OUT policy (11) becomes,

$$\begin{aligned}C[\xi] =&\mathbb{E}[h(NS_t)^+ + b(-NS_t)^+] + \mathbb{E}[A \times R_t] \\ &+ \min_{\xi} \left\{ \mathbb{E}[uk + w(P_t - k)^+] + \mathbb{E}[u_r k_r + w_r(\xi R_t - k_r)^+] + \mathbb{E}[G(1-\xi)R_t] \right\} \\ =& (h+b)\ \varphi[z_i] \sqrt{\mathbb{V}[NS]} + A\mu_r + w\ \varphi[z_p] \sqrt{\mathbb{V}[P]} + u(\mu_d - \xi\mu_r) \\ &+ w_r\ \varphi[z_r] \sqrt{\xi^2 \mathbb{V}[R]} + u_r \xi \mu_r + G(1-\xi)\mu_r, \end{aligned} \tag{B.6}$$

The first-order derivative of $C[\xi]$ w.r.t. ξ is given by

$$\frac{\partial C[\xi]}{\partial \xi} = w\varphi\left[z_p\right] \frac{\xi \mathbb{V}[R] - cov_{L+1}}{\sqrt{\mathbb{V}[P]}} + w_r\ \varphi\left[z_r\right] \sqrt{\mathbb{V}[R]} + \mu_r(u_r - u - G). \tag{B.7}$$

The second-order derivative of $C[\xi]$ w.r.t. ξ is

$$\begin{aligned}\frac{\partial^2 C[\xi]}{\partial \xi^2} &= w\ \varphi[z_p] \frac{\mathbb{V}[R]\mathbb{V}[P|\xi=0] - (\phi_d^{L+1} cov_0)^2}{\mathbb{V}[P]\sqrt{\mathbb{V}[P]}} \\ &\geq w\ \varphi[z_p] \frac{\mathbb{V}[R]\mathbb{V}[P|\xi=0] - \phi_d^{2(L+1)} \mathbb{V}[R]\mathbb{V}[D]}{\mathbb{V}[P]\sqrt{\mathbb{V}[P]}} \\ &= w\ \varphi\left[z_p\right] \frac{\mathbb{V}[R](1-\phi_d^{L+1})\sigma_d^2}{\mathbb{V}[P]\sqrt{\mathbb{V}[P]}} \frac{\left((1-\phi_d^{L+2})^2 + \phi_d^{L+1}(1-\phi_d^{L+3})\right)}{(1-\phi_d)^2} \\ &> 0,\ \text{if } 1 > \phi_d \geq 0. \end{aligned} \tag{B.8}$$

Appendix C. Deriving the CL-OUT policy

Let us begin with the following relationship (Hosoda et al., 2015) that always holds in our CLSC setting, regardless of the ordering policy present:

$$NS_{t+L+1} = NS_t + P_t + WIP_t - \left(D_{t+L+1} + \sum_{i=1}^{L} D_{t+i}\right) + PIR_t, \tag{C.1}$$

where $WIP_t = \sum_{i=1}^{L} P_{t-i}$, and PIR_t represents the pipeline inventory of the returns at time t and is $PIR_t = \xi \sum_{i=0}^{L} R_{t-i}$. The inventory position, IP_t, in period t immediately after P_t is issued is:

$$IP_t = NS_t + WIP_t + P_t + PIR_t.$$

By using the inventory balance equation (1), IP_t can be rewritten as

$$\overbrace{NS_t + WIP_t + P_t + PIR_t}^{=IP_t} = \overbrace{NS_{t-1} + \xi R_{t-(L+1)} - D_t + P_{t-(L+1)}}^{=NS_t} + \overbrace{WIP_t}^{=\sum_{i=1}^{L} P_{t-i}} + P_t + PIR_t$$
$$= NS_{t-1} + \xi R_{t-(L+1)} - D_t + WIP_{t-1} + P_{t-1} + P_t + PIR_t. \tag{C.2}$$

Rearranging (C.2) yields

$$P_t = D_t - \xi R_{t-(L+1)} + (NS_t + P_t + WIP_t) - (NS_{t-1} + P_{t-1} + WIP_{t-1}),$$

which can be rewritten further with knowledge of (C.1):

$$P_t = D_t - \xi R_{t-(L+1)} + \left(NS_{t+L+1} + \sum_{i=1}^{L+1} D_{t+i} - PIR_t\right) - \left(NS_{t+L} + \sum_{i=1}^{L+1} D_{t-1+i} - PIR_{t-1}\right), \tag{C.3}$$

which can be rewritten further with knowledge of (C.3):

$$P_t = D_t - \xi R_{t-(L+1)} \underbrace{-PIR_t + PIR_{t-1}}_{=-\xi R_t + \xi R_{t-(L+1)}} + \left(NS_{t+L+1} + \sum_{i=1}^{L+1} D_{t+i}\right) - \left(NS_{t+L} + \sum_{i=1}^{L+1} D_{t-1+i}\right)$$
$$= D_t - \xi R_t + \left(NS_{t+L+1} + \sum_{i=1}^{L+1} D_{t+i}\right) - \left(NS_{t+L} + \sum_{i=1}^{L+1} D_{t-1+i}\right).$$

Replacing the future values with their expected values yields the CL-OUT policy:

$$P_t = D_t - \xi R_t + (S_t - S_{t-1}), \tag{C.4}$$

where S_t is the target inventory position (or, the order-up-to level) at t determined as:

$$S_t = \mathbb{E}\left[\sum_{i=1}^{L+1} D_{t+i} | t\right] + \mathbb{E}[NS] = (L+1)\mu_d + \phi_d \frac{1-\phi_d^{L+1}}{1-\phi_d}(D_t - \mu_d) + TNS^{\star}. \tag{C.5}$$

Using expectation on (C.4) and (C.5) yields the expected value of P_t and ND_t:

$$\mathbb{E}[P] = \mu_p = \mu_d - \xi \mu_r = \mathbb{E}[ND]. \tag{C.6}$$

For the case of no information sharing, we need to assume further that the manufacturer does not know the values of PIR_t and PIR_{t-1} in (C.3) and replaces them with expected values, $\mathbb{E}[PIR_t|t] = \mathbb{E}[PIR_{t-1}|t-1] = \xi(L+1)\mu_r$, which yields:

$$P_t = D_t - \xi R_{t-(L+1)} + (S_t - S_{t-1}). \tag{C.7}$$

Appendix D. Net stock level variances

In this section, we will show the steps for obtaining the variance of the net stock levels. Using the inventory balance equation (2), we have:

$$P_t = NS_{t+L+1} - NS_{t+L} + ND_{t+L+1}. \tag{D.1}$$

Thus, $\sum_{i=1}^{L} P_{t-i}$ can be rewritten as:

$$\sum_{i=1}^{L} P_{t-i} = P_{t-1} + P_{t-2} + \cdots + P_{t-L} = NS_{t+L} - NS_t + \sum_{i=1}^{L} ND_{t+i}. \tag{D.2}$$

By substituting (D.2) into (12), P_t can be written as

$$P_t = \mathbb{E}[ND_{t+L+1}|t] + (TNS^\star - NS_{t+L}) + \left(\mathbb{E}\left[\sum_{i=1}^{L} ND_{t+i}|t\right] - \sum_{i=1}^{L} ND_{t+i}\right). \tag{D.3}$$

Note, $TNS^\star = \mathbb{E}[NS]$. Since (D.1) and (D.3) equal each other, we can eliminate P_t:

$$\begin{aligned} NS_{t+L+1} - \mathbb{E}[NS] &= \mathbb{E}\left[ND_{t+L+1}|t\right] - ND_{t+L+1} + \left(\mathbb{E}\left[\sum_{i=1}^{L} ND_{t+i}|t\right] - \sum_{i=1}^{L} ND_{t+i}\right) \\ &= \mathbb{E}\left[\sum_{i=1}^{L+1} ND_{t+i}|t\right] - \sum_{i=1}^{L+1} ND_{t+i} \\ &= -\sum_{i=0}^{L} \lambda_i \, \varepsilon_{d,t+L+1-i}, \end{aligned} \tag{D.4}$$

where

$$\lambda_i = (1-\phi_d^{i+1})/(1-\phi_d). \tag{D.5}$$

Eq. (D.4) is an MA(L) process with moving average coefficients λ_i ($i \in \mathbb{Z}|0 \leq i \leq L$). A detailed explanation of MA processes can be found in Box et al. (2008). As the error term, $\varepsilon_{d,t}$, is an iid process, the variance of (D.4) is given by:

$$\sigma_d^2 \sum_{i=0}^{L} \lambda_i^2. \tag{D.6}$$

Substituting λ_i (D.5) into (D.6) yields the stated expression, (15), for $\mathbb{V}[NS]$.

Appendix E. Variance and derivatives of production of new items

To obtain the variance of P_t, first we modify (13):

$$\begin{aligned}P_t =& D_t - \xi R_t + (S_t - S_{t-1})\\ =& D_t - \xi R_t + \phi_d \lambda_L (D_t - D_{t-1})\\ =& \mu_d - \xi \mu_r + ((1+\phi_d\lambda_L)\phi_d - \phi_d\lambda_L - \xi\theta_r)(D_{t-1} - \mu_d) - \xi\phi_r(R_{t-1} - \mu_r)\\ &+ (1+\phi_d\lambda_L)\varepsilon_{d,t} - \xi\varepsilon_{r,t},\end{aligned}$$

where $\lambda_L = (1-\phi_d^{L+1})/(1-\phi_d)$. Since $\mathbb{E}[P] = \mu_d - \xi\mu_r = \mathbb{E}[ND]$, see (C.6), the variance of P_t is then given by:

$$\begin{aligned}\mathbb{V}[P] =& \mathbb{E}\left[(P_t - (\mu_d - \xi\mu_r))^2\right]\\ =& \mathbb{V}[D] - 2\xi \underbrace{\frac{\theta_r\phi_d^{L+2}}{1-\phi_d\phi_r}\mathbb{V}[D]}_{=\mathrm{cov}_{L+1}} + \xi^2\mathbb{V}[R] + 2\frac{\phi_d(1-\phi_d^{L+1})(1-\phi_d^{L+2})}{(1-\phi_d^2)(1-\phi_d)}\sigma_d^2\\ =& \mathbb{V}[ND] + 2\frac{\phi_d(1-\phi_d^{L+1})(1-\phi_d^{L+2})}{(1-\phi_d^2)(1-\phi_d)}\sigma_d^2. \end{aligned} \tag{E.1}$$

Interestingly, (E.1) reveals the derivatives of $\mathbb{V}[P]$ *w.r.t.* ξ are identical to those of $\mathbb{V}[ND]$. The first and second order derivatives were provided in (18) and (19).

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